BAYESIAN CLASSIFICATION

Bayesian Belief Networks

Since in real world dependencies can exist between variables, hence *Bayesian belief networks* are used to specify joint conditional probability distributions

They allow class conditional independencies to be defined between subset of variables

They provide a graphical model of causal relationships, on which learning can be performed

These networks are also called belief networks, Bayesian networks, and probabilistic networks

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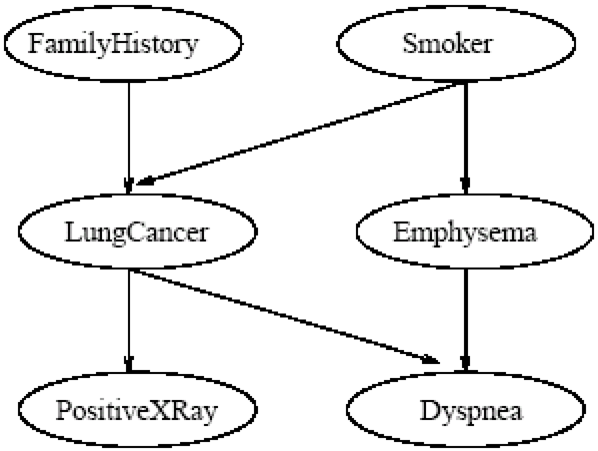
Bayesian Belief Networks

A belief network is defined by two components

The first is a directed acyclic graph, where each node represents a random variable and each arc represents a probabilistic dependence



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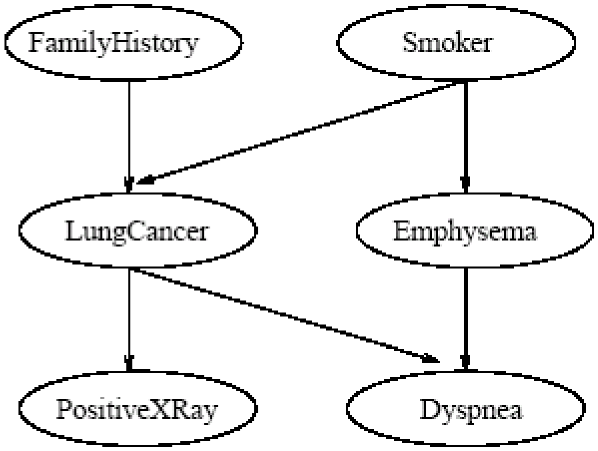
If an arc is drawn from a node Y to a node Z, then Y is a parent of Z and Z is a descendent of Y

Each variable is conditionally independent of its non descendents in the graph, given its parents

The variables may be discrete or continuous



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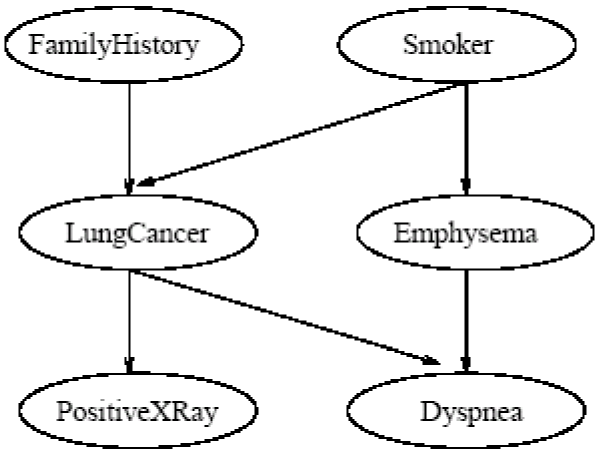
The second component of a belief network consists of a conditional probability table for each variable

For a variable Z, it specifies the conditional probability distribution P(Z|Parents(Z))

The conditional probability for each value of Z is listed for each possible combination of values of its parents



	FH, S	FH, ~S	~FH, S	~FH, ~S
LC	0.8	0.5	0.7	0.1
~LC	0.2	0.5	0.3	0.9

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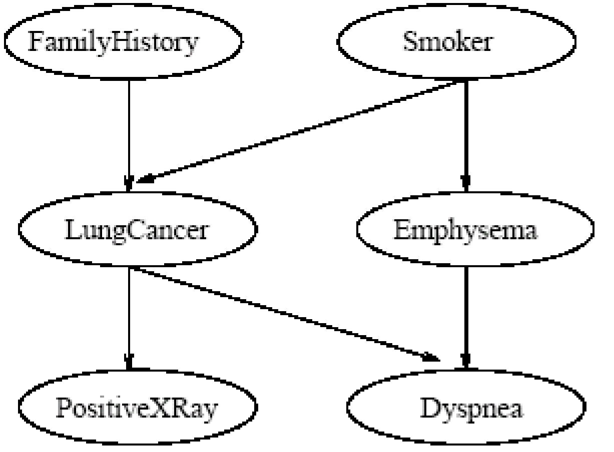
Bayesian Belief Networks

The joint probability of any tuple (z_1, …, z_n) corresponding to the attributes Z_1, …, Z_n is computed by

$$P(z_1, \ldots, z_n) = \prod_{i=1}^{n} P(z_i | Parents(Z_i)),$$



Where the values $P(z_i|Parents(Z_i))$ correspond to the entries in the CPT for z_i

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Bayesian Belief Networks

A node within the network can be selected as an output node representing a class label attribute

The structure of the network can be given by an expert

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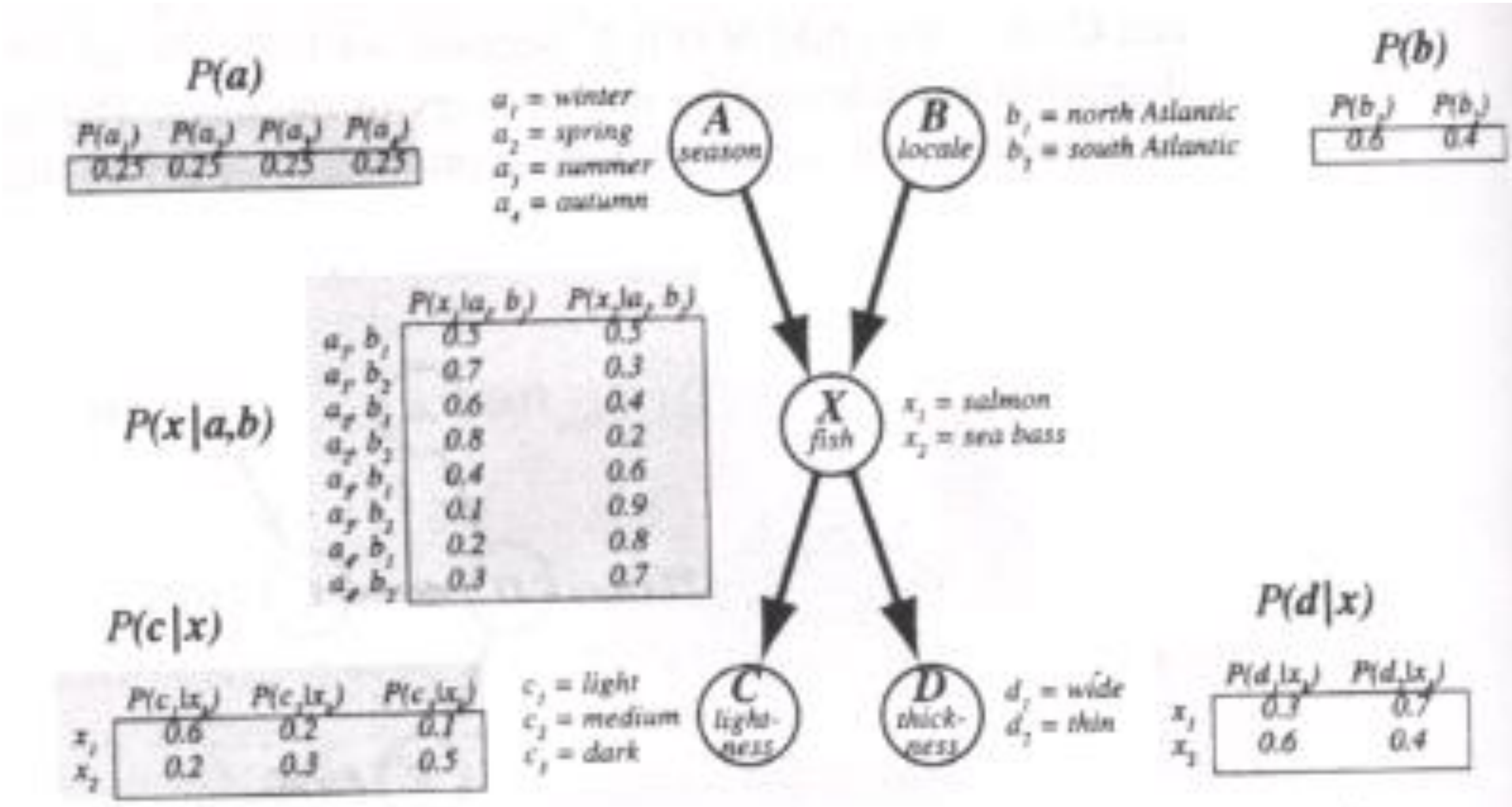

Example: probability that a fish caught in summer, in the north Atlantic, is a sea bass, and is dark and thin:

$$P(a_3, b_1, x_2, c_3, d_2)$$
$$= P(a_3)P(b_1)P(x_2|a_3,b_1)P(c_3|x_2)P(d_2|x_2)$$
$$= 0.25 \times 0.6 \times 0.6 \times 0.5 \times 0.4 = 0.012$$

Summary

Bayesian Belief Networks (BBNs), also known as Bayesian Networks or Probabilistic Graphical Models, are used to model and reason under uncertainty. BBNs combine probability theory and graph theory to represent probabilistic relationships between variables and enable probabilistic inference.

Structure:

A BBN consists of a graphical structure that represents the relationships between variables. It is typically represented as a directed acyclic graph (DAG), where each node represents a random variable, and the directed edges represent dependencies between variables.

Conditional Probability Tables (CPTs):

Each node in the BBN has an associated conditional probability table (CPT) that specifies the probability distribution of the node given its parents in the graph. The CPT describes how the variable depends on its direct causes or parents.

Bayesian Conditionalization:

BBNs use Bayesian conditionalization to update probabilities based on new evidence or observations. Given some evidence about certain variables, the network can compute the posterior probability distribution of other variables.

Inference:

BBNs enable probabilistic inference to compute probabilities of unobserved variables given evidence. There are several algorithms for performing inference in BBNs, including belief propagation, variable elimination, and junction tree algorithms. These algorithms exploit the graph structure and conditional independence relationships to efficiently compute posterior probabilities.

Learning:

BBNs can be learned from data using various methods such as maximum likelihood estimation, Bayesian parameter estimation, or constraint-based learning algorithms. Learning involves estimating the parameters of the CPTs based on observed data or expert knowledge.

Applications:

BBNs have a wide range of applications in various fields, including healthcare, finance, robotics, and decision support systems. They are used for tasks such as diagnosis, risk assessment, decision-making, and prediction under uncertainty.

By representing probabilistic dependencies and performing probabilistic inference, Bayesian Belief Networks provide a powerful framework for reasoning under uncertainty and making informed decisions based on available evidence.